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Kees E. Bouwman
Faculty of Economics, University of Groningen

Jan P.A.M. Jacobs
Faculty of Economics, University of Groningen

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Forecasting with real-time macroeconomic data: the ragged-edge problem and revisions*

Kees E. Bouwman and Jan P.A.M. Jacobs
University of Groningen

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Abstract

Real-time macroeconomic data are typically incomplete for today and the immediate past ('ragged edge') and subject to revision. To enable more timely forecasts the recent missing data have to be dealt with. In the context of the U.S. leading index we assess four alternatives, paying explicit attention to publication lags and data revisions.

Keywords: real-time data, data revisions, ragged edge, leading index, forecast evaluation
JEL-code: C53, E32, E37

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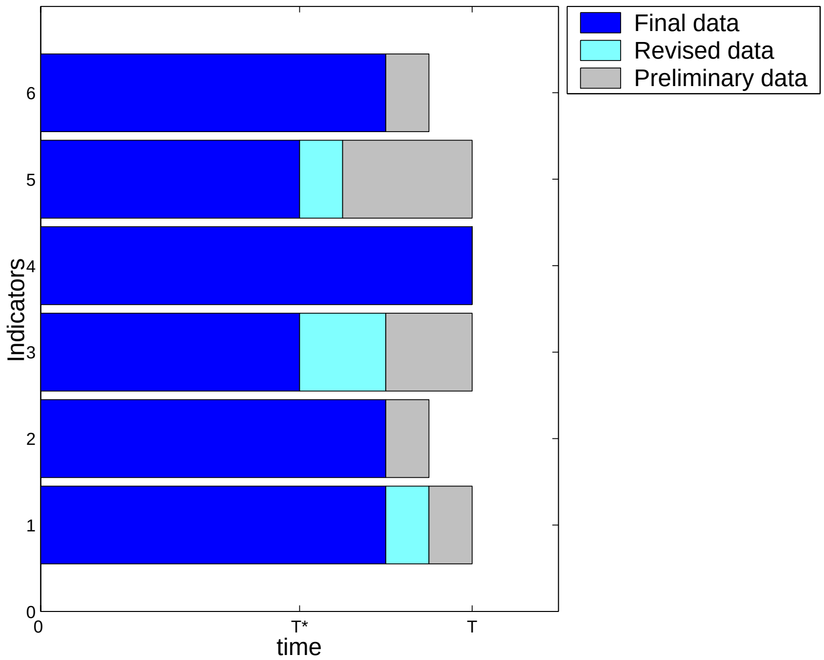
1 Introduction

Macroeconomic data are published with lags causing a ragged edge at the most recent horizon (Wallis, 1986). Furthermore the data are revised quite often. Figure 1 illustrates the problem by means of a stylized representation of the data vintage of some variables in period T. Here, the second and sixth variable are published with lags. The most recent figure of all variables is preliminary, or a first estimate; it is revised subsequently in the next vintage. The exception is the fourth variable, which is published as final data and thus not subject to revision. Interest rates are an example. Whether and when other series become final is an open question. It may take quite some time (years) before final figures are published—and even these can be revised. For example, the January 2004 vintage of the most recent update on US leading indicators shows a revision in the money supply ($M2$) series across the board from January 1959 onwards!

Problems—and opportunities—associated with real-time data analysis attract a lot of attention. Three broad areas are distinguished: data revisions, forecasting, and policy analysis. See `www.phil.frb.org/econ/forecast/reabib.html` for references. This paper focuses on the first two categories and discusses more timely forecasting with real-time macroeconomic variables which involves smoothing the ragged edge and imputation of the most recent missing observations. In addition, we explicitly take effects of data revisions into account, albeit in a simple manner.

In the context of linear time series models, delayed observations and data revisions are straightforwardly dealt with by the Kalman filter. General in-

Figure 1: Outline of the problem



troductions to the Kalman filter and state-space modelling are provided in the textbooks of Harvey (1989) and Hamilton (1994, Chapter 13). Harvey (1989, Section 8.7.2) discusses solutions for the ragged edge or delayed observations problem. Howrey (1978, 1984) is an early adopter of the methodology to model data revisions, see also Harvey et al. (1981) or Harvey (1989, Section 6.4.4). Bordignon and Trivellato (1989) present an early application of forecasting with provisional data.

We illustrate the imputation methods with the U.S. leading economic index. The system of leading, coincident and lagging business cycle indexes was developed at the National Bureau of Economic Research (NBER) in the U.S. in the 1930s, and described in the seminal book of Burns and Mitchell

(1946). Nowadays, the indexes are maintained and regularly published by The Conference Board (TCB), see The Conference Board (2001). Recently, TCB has made the U.S. leading index more timely by adopting univariate models for imputation of recent missing observations (McGuckin, Ozyildirim, and Zarnowitz, 2001). The more timely index uses available information more efficiently than the previous method by combining projected values for data missing in the publication period and actual values for the available data (McGuckin, Ozyildirim, and Zarnowitz, 2003). We find that the alternative prediction models (running in differences of the indicators) outperform the univariate imputation method adopted by TCB (in levels). In addition, including even a simple model for data revisions improves the accuracy of the predictions.

The remainder of the paper is organised as follows. Section 2 describes the methodology. Section 3 presents our application for the U.S. leading index. Section 4 concludes.

2 Methodology

Macroeconomic forecasters are often faced with a situation in which observations on some series are released somewhat later than observations on other series. We assume in this paper that the maximum publication lag is equal to one month. Let $\boldsymbol{x}_1(t)$, $t \in \mathbb{N}$, be the vector of final values for period t of the variables released without a publication lag and $\boldsymbol{x}_2(t)$ the vector of final values for period t of the variables released with an one-month publication lag.

As mentioned in the Introduction, most macroeconomic variables are subject to data revisions. The first release of a statistical agency is a provisional value that is revised in subsequent periods. More specifically, statistical agents release *data vintages* of time series representing all the agencies' knowledge on the variables. Two types of revisions can be distinguished: first, monthly updates due to additional information that becomes available, and secondly, revisions due to redefinitions.

We abstract from the latter type of revisions and assume the data become final after 5 months, so there is a maximum of five releases and four revisions for each period. Let $\boldsymbol{x}_k(i,t)$ with $k = 1, 2$ and $i = 1, \ldots, 5$ denote the i-th release of the value $\boldsymbol{x}_k$ for period t. The release period of $\boldsymbol{x}_k(i,t)$ is denoted by $\tau_k(i,t)$. In our case the release period is given by

$$\begin{aligned} \tau_1(i,t) &= t + i \\ \tau_2(i,t) &= t + i + 1. \end{aligned}$$

The fifth release is the final release, hence $\boldsymbol{x}_k(t) \equiv \boldsymbol{x}_k(5,t)$ and $\tau_k(t) \equiv \tau_k(5,t)$. Some data are revised less often, but this can easily be incorporated. For instance, if the j-th component of $\boldsymbol{x}_1$ is not revised at all, then $x_{1,j}(i,t) = x_{1,j}(t)$ for all i.

Statistical agencies typically release a new vintage every month. All values in a vintage are given by their latest available release, i.e.

$$\begin{aligned} \boldsymbol{x}_1^T(t) &= \boldsymbol{x}(\min(T - t, 5), t) && \forall t < T \\ \boldsymbol{x}_2^T(t) &= \boldsymbol{x}(\min(T - t - 1, 5), t) && \forall t < T - 1, \end{aligned}$$

where the subscript T denotes the vintage date.

All the information available in period T is represented by the information set

$$\Omega^T = \{\boldsymbol{x}_k(i,t) : \tau_k(i,t) \leq T, k = 1,2, i = 1,\ldots,5, t = 1,\ldots,T-1\}. \quad (1)$$

This information set represents all information actually available to a forecaster in a real-time setting. Most forecast evaluations ignore the problem of real-time forecasting and judge forecasts based on final data. In this situation the information set becomes

$$\tilde{\Omega}^T = \{\boldsymbol{x}_k(t) : \tau_k(1,t) \leq T, k = 1,2, t = 1,\ldots,T-1\}. \quad (2)$$

Modelling final data

Most forecasting devices require a complete data set. To smooth the ragged edge macroeconomic forecasters have two options: they can choose to delete the most recent information on the variables that are released without a publication or to predict recent missing observations of the variables that are released with a lag. The latter strategy is referred to as *more timely forecasting*. To predict recent missing observations we have to specify the dynamics of the final data itself. The first procedure, labelled TCB after its proponent The Conference Board, ignores data revisions and employs univariate AR(2) models on the levels for the imputation, so

$$\hat{\boldsymbol{x}}_1(t|\Omega_T) = \boldsymbol{x}_1^T(t) \qquad\qquad t \le T-1$$

$$\hat{\boldsymbol{x}}_2(t|\Omega_T) = \begin{cases} \boldsymbol{x}_2^T(t) & t < T-1 \\ \boldsymbol{b} + \boldsymbol{A}_1\boldsymbol{x}_2^T(t-1) + \boldsymbol{A}_2\boldsymbol{x}_2^T(t-2) & t = T-1 \end{cases}$$

where $\boldsymbol{A}_1$ and $\boldsymbol{A}_2$ are diagonal parameter matrices and $\boldsymbol{b}$ is a parameter vector arising from modeling the components of $\boldsymbol{x}_2$ separately by AR(2) models with a constant included. The parameter estimates are obtained from historical data.

The alternatives model the dynamics of the final data in terms of functions $\boldsymbol{r}_i(t)$ of $\boldsymbol{x}_i(t)$

$$\boldsymbol{r}_i(t) = g_i\left(\boldsymbol{x}_i(t)\right) \qquad i = 1, 2.$$

In particular we assume an p-th order linear model

$$\boldsymbol{r}(t) = \boldsymbol{b} + \boldsymbol{A}_1\boldsymbol{r}(t-1) + \ldots + \boldsymbol{A}_p\boldsymbol{r}(t-p) + \boldsymbol{\varepsilon}(t),$$

where $\boldsymbol{r}(t) = (\boldsymbol{r}_1(t)', \boldsymbol{r}_2(t)')'$, and the errors follows a Gaussian White Noise (GWN) process, $\boldsymbol{\varepsilon}(t) \sim GWN(0, \Sigma_\varepsilon)$.

This data model can easily be put into a State-Space (SS) framework. Defining the state vector as $\boldsymbol{\alpha}(t) = (\boldsymbol{r}(t)', \ldots, \boldsymbol{r}(t-p+1)')'$, the SS form is given by the *measurement equation*

$$\boldsymbol{r}(t) = \begin{bmatrix} \boldsymbol{I} & \boldsymbol{0} & \ldots & \boldsymbol{0} \end{bmatrix} \boldsymbol{\alpha}(t), \tag{3}$$

and the *transition equation*

$$\boldsymbol{\alpha}(t+1)=\begin{bmatrix}\boldsymbol{A}_1 & \boldsymbol{A}_2 & \dots & \boldsymbol{A}_p\\ \boldsymbol{I} & \dots & \mathbf{0} & \mathbf{0}\\ \vdots & \ddots & \vdots & \vdots\\ \mathbf{0} & \dots & \boldsymbol{I} & \mathbf{0}\end{bmatrix}\boldsymbol{\alpha}(t)+\begin{bmatrix}\boldsymbol{I}\\ \mathbf{0}\\ \vdots\\ \mathbf{0}\end{bmatrix}\boldsymbol{b}+\begin{bmatrix}\boldsymbol{I}\\ \mathbf{0}\\ \vdots\\ \mathbf{0}\end{bmatrix}\boldsymbol{\varepsilon}(t), \qquad (4)$$

where $\boldsymbol{I}$ is the identity matrix. The ragged edge can be smoothed by imputing the delayed observations of $\boldsymbol{r}_2(t)$ with the Kalman filter.

We assess the following alternative models:

AR(p) : $A_1, \dots, A_p$ and Σ_ε are restricted to be diagonal. The parameters are estimated by OLS for the individual AR(2) models; Σ_ε is formed by the variances of the residuals of the individual equations.

SUR(p) : $A_1, \dots, A_p$ are restricted to be diagonal but no restrictions are imposed on Σ_ε. The parameters are estimated by the Seemingly Unrelated Regression (SUR) procedure.

VAR(p) : $A_1, \dots, A_p$ and Σ_ε are all free. Parameters are estimated by OLS for the individual equations; Σ_ε is estimated from the residuals.

Modelling data revisions

Up to now we did not explicitly take the provisional character of our real-time data into account. In general, provisional values are good indicators of their corresponding final values and can be exploited in predicting these. The most common practice, below referred to as the naive approach, is to ignore the revision errors and focus on the imputation on the basis of last available data vintage

$$\hat{\boldsymbol{x}}_k(t|\Omega^T) = \boldsymbol{x}_k(\min(t-s+1,5),t) \text{ for } t \leq T-1.$$

In this case provisional values are considered perfect predictions for the corresponding final values. Hence, the approach does not discriminate between provisional and final values.

A more sophisticated approach takes the revision process into account and computes predictions for the final values on the basis of provisional releases and the dynamics of the final values. A typical model yields the conditional distribution of the unobserved final values given the observed provisional values. From these densities we can derive the Minimum Mean Squared Error (MMSE) predictions of the final values,

$$\hat{\boldsymbol{x}}_k(t|\Omega^T) = \mathrm{E}\left(\boldsymbol{x}_k(t)|\Omega^T\right) \quad t \leq T-1.$$

The measurement equation of the state-space framework of Equations (3) can easily be extended to incorporate the data revision process. In this paper we consider a simple measurement error model for the revision process. This model assumes that preliminary values are final values contaminated with an additive measurement error, which follows a Gaussian White Noise process. To be more specific, consider the revision errors

$$\boldsymbol{u}(i,t) = \boldsymbol{r}(i,t) - \boldsymbol{r}(i+1,t) \qquad i = 1,\ldots,4.$$

Stacking the revision errors for the j-th component in a vector, we obtain $\boldsymbol{\eta}_j(t) = (u_j(1,t), \ldots, u_j(4,t))'$. The revision model assumes

$$\begin{aligned} \boldsymbol{\eta}_j &\sim GWN(\mathbf{0}, \boldsymbol{\Sigma}_{\eta,j}), \\ \mathrm{E}\left(\boldsymbol{\eta}_j(t)\boldsymbol{\eta}_k(t)'\right) &= \mathbf{0} \qquad j \neq k, \\ \mathrm{E}\left(\boldsymbol{\eta}_j(t)\varepsilon(t)'\right) &= \mathbf{0}. \end{aligned}$$

Subsequently stacking the revision errors

$$\boldsymbol{\nu}(t) = \begin{pmatrix} \boldsymbol{u}(1,t) \\ \vdots \\ \boldsymbol{u}(4,t) \end{pmatrix},$$

yields the following variance-covariance matrix of the revision errors

$$\mathrm{E}\left(\boldsymbol{\nu}(t)\boldsymbol{\nu}(t)'\right) = \boldsymbol{K}_{10,4} \begin{pmatrix} \boldsymbol{\Sigma}_{\eta,1} & & \mathbf{0} \\ & \ddots & \\ \mathbf{0} & & \boldsymbol{\Sigma}_{\eta,10} \end{pmatrix} \boldsymbol{K}_{4,10},$$

where $\boldsymbol{K}_{m,n}$ is the commutation matrix defined such that $\boldsymbol{K}_{m,n} \operatorname{vec} \boldsymbol{A} = \operatorname{vec} \boldsymbol{A}'$ for an arbitrary $m \times n$-matrix $\boldsymbol{A}$.

Now the state-space form of the complete model is given by the *measure-*

ment equation

$$\boldsymbol{y}(t) = \left(\boldsymbol{\iota} \otimes \begin{bmatrix} \boldsymbol{I} & \mathbf{0} & \dots & \mathbf{0} \end{bmatrix}\right) \boldsymbol{\alpha}(t) + \left(\begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \otimes \boldsymbol{I} \right) \boldsymbol{\nu}(t), \quad (5)$$

where $\boldsymbol{y}(t) = (\boldsymbol{r}(1,t)', \dots \boldsymbol{r}(5,t)')'$, $\boldsymbol{\iota}$ is the unit vector of length 5, and the transition equation (4). Again, we can set the Kalman filter to work to impute the delayed observations $\boldsymbol{r}_2(t)$. However, since the revision model recognizes the provisional nature of the latest data, predictions of the final data, $\hat{\boldsymbol{r}}_1(t|\Omega^T)$ and $\hat{\boldsymbol{r}}_2(t|\Omega^T)$, generally differ from the provisional values and should be used in forecasting instead.

Leading economic indexes

Below we assess the imputation methods with the U.S. leading economic index. The construction of a Leading Economic Index (LEI) from its individual indicators can be summarized by the following two steps. First, differences or symmetric growth rates of the individual indicators are computed, i.e.

$$\boldsymbol{r}_1(t) = g_1(\boldsymbol{x}_1(t))$$

$$\boldsymbol{r}_2(t) = g_2(\boldsymbol{x}_2(t))$$

Secondly, these transformed indicators are turned into a LEI by taking a weighted linear combination

$$I_B(t) = f(\boldsymbol{r}_1(t), \boldsymbol{r}_2(t)).$$

More details are provided in Section 3 below. In this case the index is calculated based on final values. This index will be referred to as the *Benchmark LEI*. Of course, the Benchmark LEI can also be expressed as a function of the levels of the indicators

$$I_B(t) = h(\boldsymbol{x}_1(t), \boldsymbol{x}_2(t)).$$

A more timely LEI produced at time T uses all available information up to that period to produce predictions of the final values of $\boldsymbol{x}_1$ and $\boldsymbol{x}_2$, $\hat{\boldsymbol{x}}_1(t|\Omega^T), \hat{\boldsymbol{x}}_2(t|\Omega^T)$. Thus in general a vintage T of the LEI is given by

$$I^T(t) = h\left(\hat{\boldsymbol{x}}_1(t|\Omega^T), \hat{\boldsymbol{x}}_2(t|\Omega^T)\right), \qquad t = 1, \ldots, T-1.$$

The last five values of the more timely index are provisional data, since they are based on the prediction of the final data. So, we have six releases of the LEI

$$I(i,t) = h(\hat{\boldsymbol{x}}_1(t|\Omega^{T+i}), \hat{\boldsymbol{x}}_2(t|\Omega^{T+i})) \qquad i = 1, \ldots, 6.$$

The first release is based on imputed data for the delayed observations $\boldsymbol{x}_2$. The sixth release is final, i.e. $I(6,t) = I_B(t)$. All earlier releases are provisional and can be considered predictions of the Benchmark LEI. The predictions $\hat{\boldsymbol{x}}_1(t|\Omega^T)$ and $\hat{\boldsymbol{x}}_2(t|\Omega^T)$ are generated by a model as explained above.

Forecast evaluation

The first five releases of the LEI can be considered forecasts of the Benchmark LEI, and typically depend on the imputation method. On order to assess the quality of the imputations methods, we compare these provisional releases to the benchmark. We consider prediction errors in symmetric differences of the LEI, i.e.

$$RI(i,t) = 2\frac{I(i,t) - I(i,t-1)}{I(i,t) + I(i,t-1)},$$

because they best represent the predictive content of the LEIs. We summarize the prediction errors by the Root Mean Squared Error (RMSE)

$$RMSE(i) = \sqrt{\sum_{t=1}^{n} \frac{1}{n} \left(RI(i,t) - RI_B(t)\right)^2}$$

and the Mean Absolute Error (MAE)

$$MAE = \sum_{t=1}^{n} \frac{1}{n} |RI(i,t) - RI_B(t)|.$$

In addition we compare different forecasts by means of Theil's U and the Diebold-Mariano test statistic. Theil's U measures the relative forecasting performance of two forecasts

$$U = \frac{RMSE_1}{RMSE_2}.$$

A value of U smaller than one corresponds to the first forecast having a smaller RMSE than the other.

Diebold and Mariano (1995) developed a test for the equality of forecast accuracy of two forecasts under general assumptions. The null hypothesis is that the expectation of an arbitrary loss differential is equal to zero

$$\mathrm{E}[d_t] \equiv [g(e_{1t}) - g(e_{2t})] = 0,$$

where we take the quadratic loss function for g. The test statistic is defined as

$$DM = \frac{\bar{d}}{\sqrt{2\pi \hat{f}_d(0)/n}},$$

where $\bar{d}$ is the sample mean of the loss differential d_t, $\hat{f}_d(0)$ is an estimate of spectral density of the loss differential at the zero frequency, and n is the number of forecasts. The DM statistic has an asymptotic standard normal distribution under the null hypothesis. For the quadratic loss function Harvey, Leybourne, and Newbold (1997) modified the DM statistic to correct for small samples

$$DM^* = \left[\frac{n + 1 - 2h + h(h-1)/n}{n}\right]^{\frac{1}{2}} DM,$$

assuming h-step ahead forecasts. The modified DM statistic follows Student's t-distribution with $n - 1$ degrees of freedom under the null hypothesis.

3 Application: the U.S. leading economic index

The TCB leading economic index has ten components or indicators. The indicators are listed in Table 1. Three indicators become available with a lag of one month: manufacturers' new orders for consumer goods and materials, manufacturers' new orders, nondefense capital goods, and the money supply, M2.

Table 1: TCB leading indicators

Average weekly hours, manufacturing
Average weekly initial claims for unemployment insurance
Manufacturers' new orders, consumer goods and materials
Vendor performance, slower delivery diffusion index
Manufacturers' new orders, nondefense capital goods
Building permits, new private housing units
Stock prices, 500 common stocks
Money supply, M2
Interest rate spread, 10-year Treasury bonds less Federal funds (%)
Index of consumer expectation

Note: indicators with one-month publication lag in italic
Source: TCB *Business Cycle Indicators Handbook*

The real-time data set consists of vintages of the indicators. The first vintage, January 1989, runs from January 1959 up to and including December 1988. The final vintage in our data set, the December 2003 vintage, has data from January 1959 up to and including November 2003. The three series that become available with a lag of one month are of course one month shorter.

The leading index is based on a weighted average of the indicators. For details see The Conference Board (2001, Section IV). Month-to-month changes are computed, standardized and added across the components for each month. Values of the index are then calculated by chaining these changes from an initial value of 100 in the first period (January 1959) and rebasing the whole series to average 100 in 1960, our base year. Standardization factors are adjusted once a year in mid-December, when TCB makes benchmark revisions to bring the index up-to-date with the indicators. In our empirical analyses below, we apply fixed weights in particular the standardization factors of TCB (2001, Table 7).

Since we are interested in smoothing the ragged edge for the most recent observations, we abstract from revisions due to redefinitions, the benchmark revisions. We construct our own real-time data set by adjusting the final vintage subsequently adding revision errors to the final values of the transformed indicators.

Final data

We evaluate the four prediction methods for final data and for real-time data. We begin with the estimation of the model parameters (including covariances) on the sample January 1959 up to and including December 1994, predict the January 1995 values of the indicators $\boldsymbol{x}_2$ for final data and calculate the leading indexes. Then we reestimate the model for January 1959–

January 1995, and calculate predictions and the leading index for February 1995. We continue this procedure up to and including the June 2003 leading indexes. Thus we obtain series of LEIs of the four prediction models TCB, AR, VAR, and SUR. The order of the models is set at two lags, corresponding to the AR order employed by TCB.

Table 2: Forecast evaluation: final data

	TCB	AR	SUR	VAR
RMSE	0.30	0.28	0.28	0.27
MAE	0.23	0.21	0.21	0.21
U		0.93	0.93	0.92
DM*		3.22	1.68	1.94
p-values		[0.00]	[0.05]	[0.03]

Table 2 shows forecast evaluation outcomes based on final data. We conclude that all three alternatives yield better LEIs than the more timely TCB index. Especially the outcomes of the Diebold-Mariano test lead to this conclusion. The null of equal forecast accuracy is rejected for every alternative. Note that the Diebold-Mariano outcomes cannot be compared to each other; the higher DM value for the AR model does not imply better forecasts than the VAR or the SUR system. The Diebold-Mariano test statistic of equal forecast accuracy of the VAR (SUR) versus the AR is 0.53 (0.15) with a p-value of 0.30 (0.44), so equal forecast forecast accuracy of the systems VAR and SUR versus the univariate AR is not rejected.

Real-time data

In the real-time analysis forecasts are based on data truly available to the forecaster at the time the forecasts are made, so on the real-time information set Ω^T of Equation (1) instead of the final data set $\tilde{\Omega}^T$ of Equation (2). For the analysis of real-time data, we estimate the model again for rolling windows as above.

Table 3: Evaluation of first releases

	TCB	AR	SUR	VAR	AR Rev	SUR Rev	VAR Rev
RMSE	0.31	0.30	0.29	0.29	0.28	0.27	0.27
MAE	0.24	0.23	0.22	0.22	0.22	0.21	0.21
U		0.95	0.94	0.92	0.90	0.87	0.86
DM*		3.79	1.69	2.30	4.16	3.02	3.09
p-values		[0.00]	[0.05]	[0.01]	[0.00]	[0.00]	[0.00]

Note: AR (SUR, VAR) Rev stands for the combination of AR (SUR, VAR) and our model for data revisions. Theil's U and the DM* statistic compare the forecasts of our imputation models to TCB.

Table 3 shows the outcomes of the evaluation of first releases of the LEI in real-time. Columns 2–4 list the outcomes ignoring data revisions, whereas the last three columns take aboard our simple model for data revisions. We reach the same conclusion as in the final data analysis and observe that all alternative models outperform the TCB procedure, although reductions in terms of the forecast evaluation statistics (RMSE, MAE) are small. However, the Diebold-Mariano tests still reject the null of equal forecast accuracy compared to TCB. Again, the high DM value of the AR model against TCB does not imply better forecasting accuracy than the SUR and VAR systems. Additional Diebold-Mariano tests of SUR and VAR against AR forecasts give DM statistics of 0.27 and 0.86 with p-values of 0.40 and 0.20, so the null hypothesis of equal forecast accuracy is not rejected for these cases.

The final three columns of Table 3 demonstrate that inclusion of a model for data revisions further reduces the RMSE and MAE statistics. Table 4 supports the observation that models with explicit attention for revisions outperform their naive counterparts. Testing the null of equal forecast accuracy among all prediction models leads to a rejection (at the 1% level) in favour of the models with attention for data revisions.

Table 4: Evaluation of first releases: impact of modelling revisions

	AR		SUR		VAR	
	Naive	Rev	Naive	Rev	Naive	Rev
RMSE	0.30	0.28	0.29	0.27	0.29	0.27
MAE	0.23	0.22	0.22	0.21	0.22	0.21
U		0.95		0.93		0.93
DM*		4.04		4.70		3.92
		[0.00]		[0.00]		[0.00]

Note: columns labelled Naive do not model data revisions, contrary to columns labelled Rev. Theil's U and the DM* statistic test the impact of including the revision model.

Table 5 compares the second to the fifth release of the LEIs in real-time. Although no actual imputation of the most recent missing observation for the indicators $\boldsymbol{x}_2$ is required here, the inclusion of a revision model generally leads to predicted final values that differ from their provisional counterparts. More specifically, the revision model recognises the additional uncertainty associated with provisional data and thus relies more on last observed final data. Therefore, an LEI based on predicted final values might outperform its naive equivalent. This is not the case in our application. The outcomes show that the naive model in not inferior to the AR, VAR and SUR models with data revisions. Our simple measurement error model is probably not sophisticated enough to increase the quality of the second to the fifth release of the LEIs.

Table 5: Impact of modelling revisions on second to fifth release of LEI

Release		Naive	AR Rev	SUR Rev	VAR Rev
2	RMSE	0.07	0.07	0.07	0.07
	MAE	0.05	0.05	0.05	0.05
	Theil's U		1.00	1.03	1.03
	Diebold-Mariano		−0.09	−0.54	−0.61
			[0.54]	[0.70]	[0.73]
3	RMSE	0.04	0.04	0.04	0.04
	MAE	0.03	0.03	0.03	0.03
	Theil's U		1.06	1.06	1.06
	Diebold-Mariano		−0.79	−0.88	−0.88
			[0.78]	[0.81]	[0.81]
4	RMSE	0.03	0.03	0.03	0.03
	MAE	0.02	0.02	0.02	0.02
	Theil's U		1.05	1.04	1.05
	Diebold-Mariano		−0.63	−0.54	−0.68
			[0.73]	[0.70]	[0.75]
5	RMSE	0.02	0.02	0.02	0.01
	MAE	0.01	0.01	0.01	0.01
	Theil's U		1.12	1.12	0.87
	Diebold-Mariano		−2.06	−1.95	−2.03
			[0.98]	[0.97]	[0.98]

4 Conclusion

This paper deals with problems associated with real-time forecasting. In particular, we employ a state-space framework to handle the ragged edge and data revisions simultaneously. An application to the U.S. leading economic index shows the potential of our method. The TCB procedure to make the LEI more timely can be improved upon by adopting a univariate and two multivariate prediction models running in differences of the indicators. Besides, including even a simple data revision model improves the accuracy of the forecasts.

A univariate model only uses its own observed past in making predictions for the delayed observations, while multivariate models take aboard all available recent information. Therefore it comes as a surprise that the multivariate models (SUR and VAR) are not superior to the univariate alternative. A possible explanation might be the short publication lag, resulting in the loss of a relatively limited amount of information in a univariate model over multivariate models. Many countries face longer publication delays, making our framework to deal with delayed observations and revisions, especially using multivariate models, even more attractive.

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